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Sensor resources deployment in a two-dimensional geographic grid is analyzed under the assumption that the intruder has perfect knowledge of the detection capabilities of the deployed sensors and associated systems. This situation represents a "worst-case" scenario for the sensor system. Dynamic programming techniques are used to calculate the optimal escape/evasion routes, which are then displayed as two dimensional path plots. The average instantaneous probabilities of detection and the cumulative probabilities of detection along possible paths are represented by computer-generated bar charts. Additional statistics concerning path characteristics are also available. For the purpose of comparing the optimal escape/evasion paths with other sub-optimal paths, the analyses of coherent linear paths, random linear paths and constrained random paths are also available. Other uses for the model are also discussed.

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MATHEMATICAL AND COMPUTER MODELLING

(Formerly Mathematical Modelling)

EDITORS-IN-CHIEF

Ervin Y. Rodin   Xavier J.R. Avula

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ANALYSIS OF SENSOR RESOURCES DEPLOYMENT
IN AN ESCAPE/EVASION SCENARIO

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Abstract. Sensor resources deployment in a two-dimensional geographic grid is
analyzed under the assumption that the intruder has perfect knowledge of the
detection capabilities of the deployed sensors and associated systems. This situation
represents a "worst-case" scenario for the sensor system. Dynamic programming
techniques are used to calculate the optimal escape/evasion routes, which are then
displayed as two dimensional path plots. The average instantaneous probabilities of
detection and the cumulative probabilities of detection along possible paths are
represented by computer-generated bar charts. Additional statistics concerning
path characteristics are also available. For the purpose of comparing the optimal
escape/evasion paths with other sub-optimal paths, the analyses of coherent linear
paths, random linear paths and constrained random paths are also available. Other
uses for the model are also discussed.

Keywords. Dynamic programming; probability of detection; sensor deployment.

INTRODUCTION

Consider the deployment of stationary sensor
resources in a two-dimensional geographic grid by
a defensive (fixed position) force in response to a
possible escaping/evading (mobile) force. These
sensors may be land-based, water-based or even
satellite-based. The term sensor is used to
represent a wide variety of devices and device
types, ranging from simple detection devices to
such devices as land mines that are designed to
destroy the mobile force. For each point on the
grid we associate a probability of detection. For a
mine field we would discuss a probability of
detonation, as opposed to a probability of detection
and would generate a probability of detonation grid
instead of a probability of detection grid. For
simplicity we will limit this discussion to
terminology dealing with detection. The analysis
of the probability of detection grid yields a
measure of overall effectiveness for the sensor
system.

A typical analysis of a two-dimensional geographic
probability of detection grid may involve viewing
the problem as a finite set of possible paths through
the grid. Each path would have to be evaluated to
generate a measure of effectiveness for the sensor
field. However, as the sensor grid grows linearly
in size, the number of possible paths to be examined
may grow at a combinatorial rate, making this
method impractical. For this reason the analysis
more commonly involves some type of
probabilistic averaging scheme over paths through
the field, or within subregions of the field itself.
Areas may be generated around the sensor field,
where the average probability of detection inside is
above some specified value. Or the analysis may
involve generating some type of random path
through the field and providing statistics about
large numbers of those paths.

For this study we will examine a 400 X 400 probability of detection grid (see Figure 1), with an intruder attempting to transverse the field from West to East subject to the restriction that the field is to be crossed by a 399 step path where the direction moved at each step is either NE, E, or SE and such that all steps are restricted to the grid. The code bar at the bottom of the plot indicates the value of the instantaneous probabilities of detection at each of the points on the grid. This probability of detection grid was generated by a dynamic simulation program for synthetic sensor coverage patterns, using a logarithmic decay function. In the sample grid, it is apparent that there are five sensors. They are located where the value of probability of detection is high surrounded by concentric circles of rapidly decreasing value.

FIG. 1. Sample Grid

<.1 .1 .2 .3 .4 .5 .6 .7 .8 .9
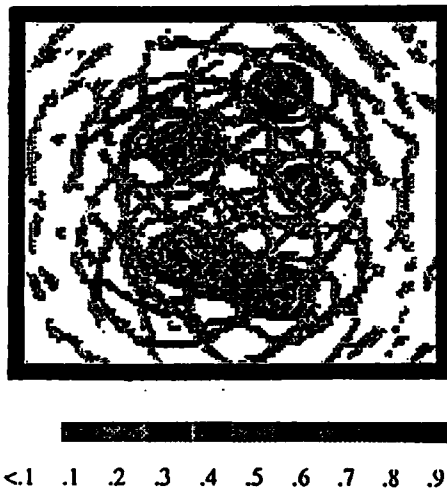
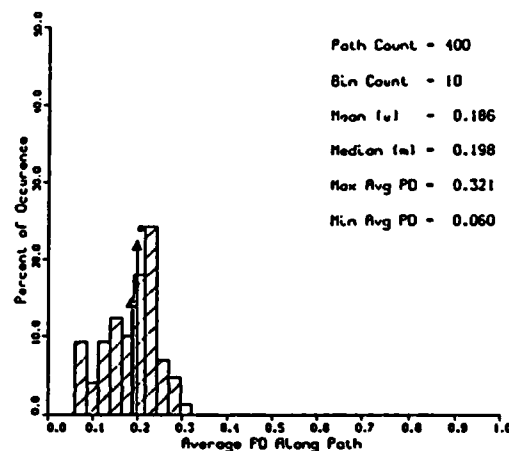### THREE PROBABLISTIC MEASURES OF EFFECTIVENESS

The "best-case" scenario for the sensor field is that the one making the transit has no knowledge of the sensor field, and thus, transits the sensor field in a non-evasive manner. The most non-evasive manner to transit a sensor field is in a straight line. Two types of linear paths can be defined : coherent linear and random linear. A constrained random walk represents a family of paths which are not subject to the straight line restriction.

Coherent linear paths are defined as those paths which correspond to a horizontal row in the probability of detection grid. Random linear paths are defined as straight line paths made by the generation of two random numbers representing

the end points of a line. One of the numbers is used as the starting row in column one of the input probability of detection grid, and the other is the ending row in the last column of the grid.
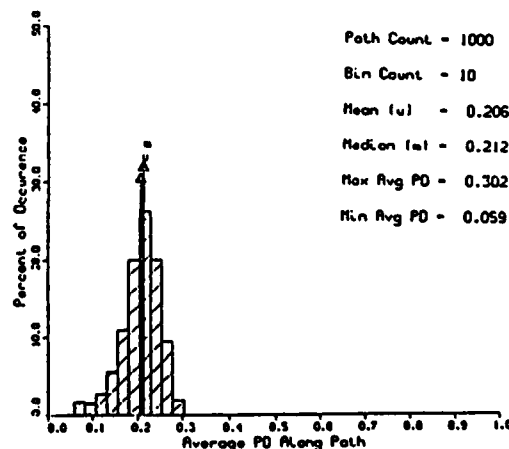
In Figure 2, the results of coherent linear transit through the grid is reported in terms of the average probability of detection along the path. The legend reports the number of paths analyzed (400), the number of bins used in the distribution (10), the mean and median, and the maximum and minimum values encountered. The mean of 0.186 and the median of 0.198 are also represented on the bar chart.

FIG. 2. Coherent Linear E/W Paths

Path Count - 400
Bin Count - 10
Mean (u) - 0.186
Median (m) - 0.198
Max Avg PD - 0.321
Min Avg PD - 0.060

Linear random transversals are approximated by a series of NE, E and SE movements supported by the model. The analysis of 1000 randomly selected paths is given in Figure 3.
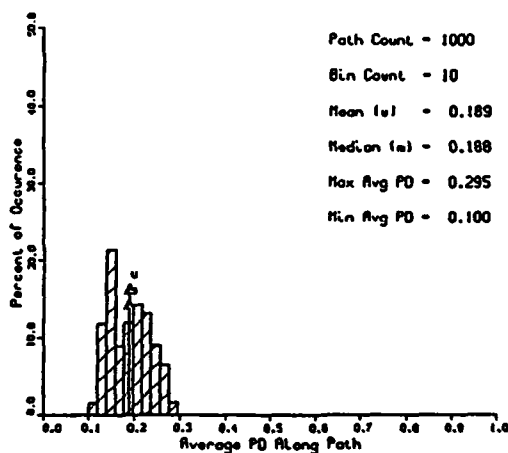
FIG. 3. Linear Random E/W Paths

Path Count - 1000
Bin Count - 10
Mean (u) - 0.206
Median (m) - 0.212
Max Avg PD - 0.302
Min Avg PD - 0.059

The sample grid appears to be a marginal sensor placement with a mean and median of 0.206 and 0.212 respectively. Again, the analysis is done using average probability of detection. Even though the linear random analysis tends to give emphasis to sensors placed at the center of the grid, the results very nearly mimic the coherent linear analysis.

Figure 4 yields the results of one thousand constrained random walks through the grid. With a mean of 0.189 and a median of 0.188 the results are again similar, even though the method gives emphasis to detection probabilities found in the "central" rows. The paths were generated by selecting with equal probability, at each stage in the development of the path, the next direction of travel from the three directions (two if on top or bottom row of grid) supported by the model.

FIG. 4. Constrained Random Walk E/W Tracks

Path Count = 1000

Bin Count = 10

Mean (u) = 0.189

Median (m) = 0.188

Max Avg PD = 0.295

Min Avg PD = 0.100

These three probabilistic measures of the sensor fields' detection capabilities yield approximately the same results. While this is comforting, it may also lead to false conclusions about the strength of the field if the assumption that the intruder has no knowledge of the field is violated.

WORST-CASE ANALYSIS

Now consider a situation where the intruder has knowledge of the sensor field capabilities. Clearly, an intruder with information concerning sensor deployment should be more effective in crossing the grid than an intruder that has none. In these instances, the "worst-case" scenario analysis is required. Consider the possibility that the intruder has perfect knowledge of the detection capabilities of the deployed sensors and associated systems. In this situation, the probabilistic analysis methods

previously described will yield values that significantly overestimate the probability of detection.

This "worst-case" scenario analysis can be evaluated by dynamic programming techniques. The methodology of dynamic programming can be used to generate, display, and analyze the optimal escape/evasion routes. This dynamic programming methodology has been successfully used by others to determine optimal shipping routes and to establish oil transport pipeline placement. Low-cost shipping routes and strategies for minimizing the cost of shipping oil through pipeline networks are analogous to low probability of detection routes through a sensor field.

Thus, a measure of sensor field effectiveness against not only an intruder who has stumbled into the sensor field, but also against an intruder with perfect knowledge of the detection capabilities of the sensor system is provided. In addition, the same approach can be used to provide a way to determine how much damage would be done in the event of disclosure of various details concerning the sensor field.

OPTIMAL PATH ANALYSIS

The grid illustrated in Figure 1 was analyzed using the methodology of dynamic programming in order to determine the west-to-east path or paths through the grid that yield the lowest possible probability of detection. The results shown in Figure 5 indicate that multiple optimal paths lie above the sensors. Once determined, the optimal paths seem sensible: avoid the areas of concentrated sensors.
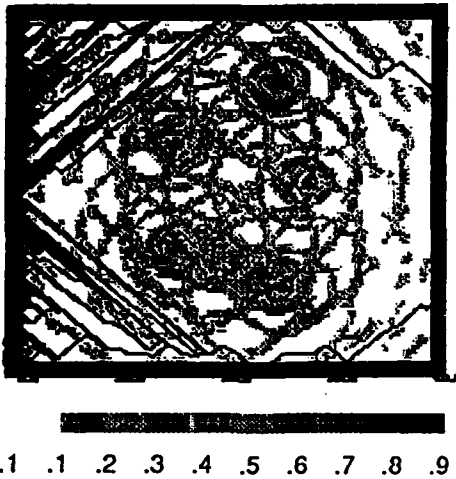
FIG. 5. Optimal Paths
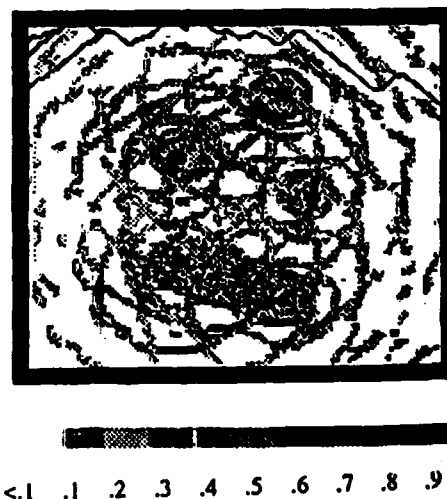
   <.1   .1   .2   .3   .4   .5   .6   .7   .8   .9

FIG. 6. Optimal Paths From All Possible
Start Locations

`<.1  .1  .2  .3  .4  .5  .6  .7  .8  .9`

Analysis of a cost grid using dynamic programming can generate optimal paths from any specified start location. In Figure 6, the optimal paths from all possible start locations are shown. Intuitively, one would avoid the center of the sensor field, and this is borne out by the plot. Note that although there are many possible start locations, optimally they merge into two distinct paths. These paths may indicate possible choke points to sensor placement personnel and are a valuable result of the analysis. These results were analyzed in the same fashion as the three previously described probabilistic methods and are given in Figure 7. If the average probability of detection along the path is an accurate estimate of the sensor field performance, the prospects of detecting a knowledgeable, intelligent transit through the sample grid are dismal. With a maximum average probability of detection of 0.028 and a mean of
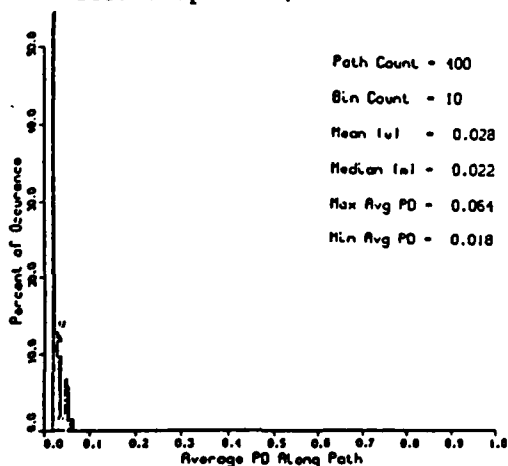
0.022, crossing the grid safely is not difficult. A comparison of Figures 2 and 7 yields a vivid reminder of the value of information concerning the fields' detection capabilities.

The grid was analyzed again with an additional restriction. Initial runs indicated that the optimal paths skirted the edges of the plots, avoiding the areas of concentrated sensors. Consequently, the analysis was restricted to minimum and maximum sensor field rows. This forced traversal through the center of the sensor field to a higher degree than was evident in either the linear random or constrained random methods reported in Figures 3 and 4, respectively. Results are shown in Figure 8. The artificial boundaries are shown as dotted horizontal lines. The optimal paths, no longer allowed to skirt the edges of the sensor field, go carefully between the sensors, as one might expect.

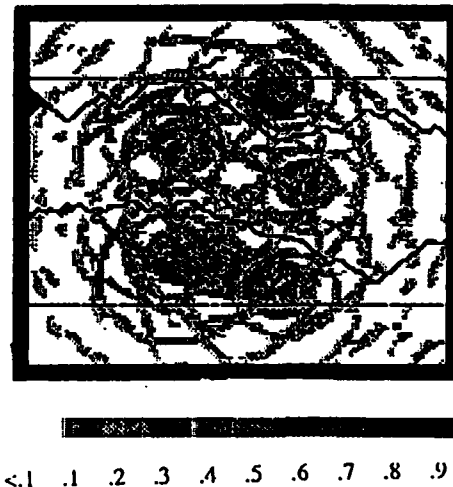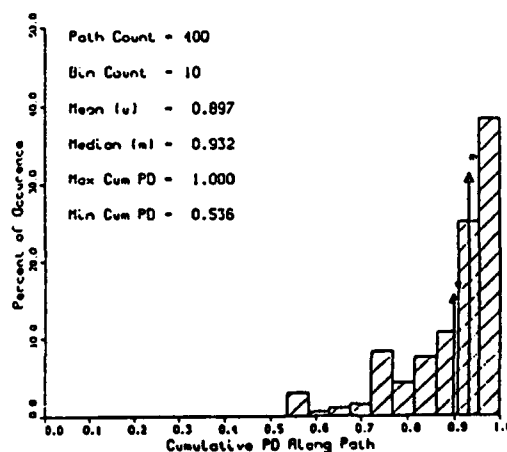FIG. 8. Optimal Paths Through Moderately
Restricted Sample Grid

`<.1  .1  .2  .3  .4  .5  .6  .7  .8  .9`

FIG. 7. Optimal E/W Tracks

Path Count = 100
Bin Count = 10
Mean (u) = 0.028
Median (m) = 0.022
Max Avg PD = 0.064
Min Avg PD = 0.018

FIG. 9. Coherent Linear E/W Tracks

Path Count = 100
Bin Count = 10
Mean (u) = 0.897
Median (m) = 0.932
Max Cum PD = 1.000
Min Cum PD = 0.536

If a different measure of effectiveness along the path is used (in this case, the cumulative probability of detection), then the results are somewhat different. As can be seen in Figure 9, coherent linear traversal results in almost certain detection, as does linear random traversal (Figure 10) and constrained random (Figure 11).

FIG. 12. Optimal E/W Tracks
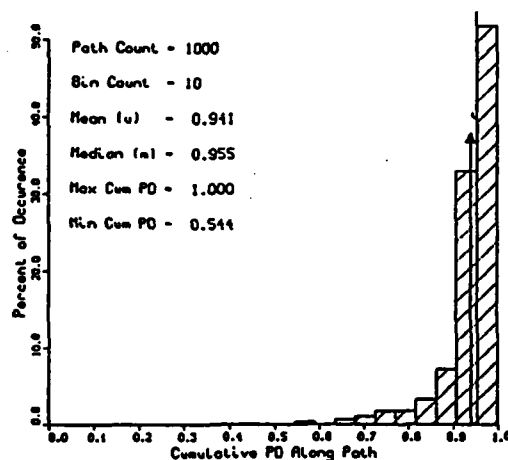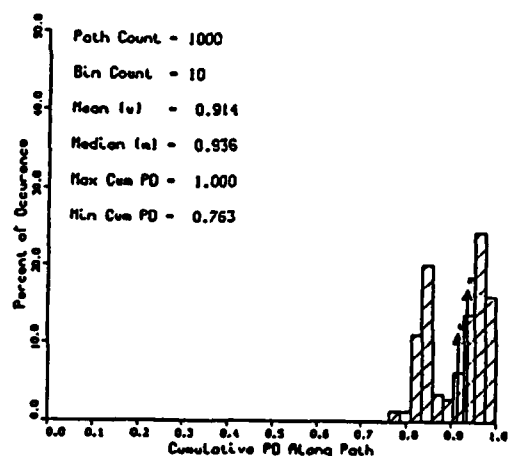

FIG. 10. Linear Random E/W Tracks

FIG. 11 Constrained Random Walk E/W Tracks

The data presented in Figure 12 for the cumulative probability of detection for optimal traversals paint a different picture. If the cumulative probability of detection along the path is an accurate estimate of the sensor field performance, the prospects of detecting a knowledgeable, intelligent transit are affected dramatically. The analysis indicates that the minimum cumulative probability of detection is a low 0.268 value and the mean is a marginal 0.374 value. Thus, crossing the grid safely with full knowledge of the sensor field has become very probable.
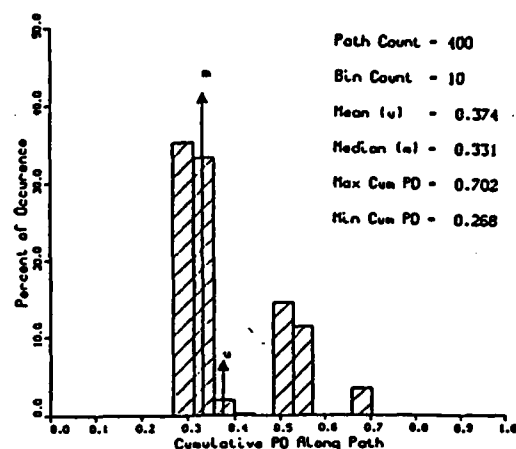
CONCLUSIONS

Analysis of a probability of detection grid yields a measure of effectiveness for the overall sensor system. A typical analysis of a two-dimensional geographic probability of detection grid may involve one of a number of the more commonly used probabilistic-type averaging schemes over paths through the field.

However, these probabilistic methods may not be acceptable for those sensor systems where a measure of effectiveness other than average or random is required. If the intruder has partial or complete knowledge of a sensor system, then analysis of the "worst-case" scenario may be required. The "worst-case" scenario analysis can be done using dynamic programming techniques. The methodology of dynamic programming can be used to generate, display, and analyze optimal escape/evasion routes.

Thus, a measure of sensor field effectiveness against not only an intruder who has stumbled into the sensor field, but also against an intruder with knowledge of the detection capabilities of the sensor system is provided.

A comparative study of a single probability of detection field grid has been made using not only optimal path analysis, but also other suboptimal techniques. The results indicate that simpler methods of analysis may not be indicative of overall sensor field performance. Additionally, the optimal path dependence on the sensor placement is made evident, further indicating the usefulness of the dynamic programming technique to sensor placement/deployment analysis.